**Attribution Modeling in Digital Advertising: An Empirical Investigation**

**Abstract**

Despite efficiency gains in Web-based data recording and management related technologies, measuring the success of a digital advertising campaign is stymied by the difficulty in attributing the value of online investment to various online channels. In a purchase funnel, a consumer may interact with an assortment of ad platforms ranging from display ads, paid search and organic search to social media and email. In this study, we consider attribution models that can be applied to assign sales credit to these and other online channels. Using an online firm’s conversion data, we investigate both heuristic and statistics-based multi-channel attribution models to see whether these models give channel valuations that differ from the commonly used last-click model. Our findings reveal wide differences between the online channels investigated. There is a striking drop in the value of display ads when we move away from the current last-click model to the other attribution models. Online marketing tools such as organic and search instead receive higher credit under these multi-channel models. The findings provide insights into the complexities of attribution modeling, and how one can choose an appropriate model based on its underlying assumptions and stability characteristics. Our results also shed light on the convergent validity of the multi-channel models, as well as the predictive ability of the statistical model.

**Keywords:** Attribution modeling; Purchase funnel; Last-click; Multi-channel attribution models; Display ads

**Introduction**

Digital advertising campaigns are often launched across multiple channels, a selection of which may include search, display ads, social media, mobile, video, and email. By exposing consumers to advertisement impressions, these channels assist to make purchase decisions, or sign up to an advertised service (Yang and Ghose, 2010; Fulgoni, 2016). To gauge the effectiveness of such advertising campaigns, it is necessary to know which media channels or advertising formats have contributed to a purchase conversion. This is a process known as attribution. A better understanding of this process or assigning conversion credit to the various relevant channels can serve a number of research and industry purposes. For example, marketing managers may use such attribution models to interpret the influence of advertisements on consumer behavior and optimize their advertising campaigns.

Early academic research into attribution modeling mainly focused on click-through rates (CTR) as an effective measure of performance (Ansari and Mela, 2003). However, digital advertising soon faced a conundrum as several studies conducted during the early 2000s reported that CTRs were in fact declining fast (Manchanda, Dube and Goh, 2006). Chatterjee, Hoffman and Novak (2003) discovered that only a small proportion of visits translated into final purchase. This inevitably cast doubt over the capacity of digital advertising as an effective mode of reaching consumers and whether it can substitute for offline advertising such as TV and newspapers. These findings also made the headline that banner advertising was not an effective online media strategy (Goldfarb and Tucker, 2011). Against this background, some practitioners began advocating the use of traditional measures of advertising effectiveness, such as awareness and recall in relation to the performance impacts of digital ad performance (Fulgoni, 2016; Manchanda, et al., 2006). Academics also showed interest in investigating the impact of display ads on long-term brand awareness and similar other performance measures (Goldfarb and Tucker, 2011). A related stream of research measured changes in brand attitudes, brand awareness, and purchase intentions as a function of ad exposure (e.g. Manchanda, et al., 2006; Fulgoni, 2016). However, since these brand choice models excluded purchase incidences from their analyses, they could not be used to evaluate the impact of display ads in the consumer journey. A potentially more interesting line of research has since examined the workings and institutional features of differentadvertising formats (e.g. display): for example, Athey and Gans (2010) investigate the potential of targeted digital advertising by considering how new media channels may create entirely new consumer markets. Recent research using these and other similar measures of performance suggests that banner ads can indeed be an effective form of advertising (Kireyev, Pauwels and Gupta, 2016; Blake, Nosko and Tadelis, 2015). In a study of the relationship between banner ads and consumer purchase patterns, Manchanda, et al. (2006) find that banner ads can play a significant role in customer retention. Furthermore, by estimating a purchase incidence advertising response model with individual-level response parameters, they show that exposure to banner ads increases the purchase probabilities for current customers.

As attribution modeling has only begun to receive increased attention in academia and practice alike, concerns remain over the development of an appropriate performance measurement system for digital advertising. The last-click method of attribution is flawed as it fails to take account of the influence of all touch points except the last one (Moe and Fader, 2004) and so does not capture the full value of digital advertising (eMarketer, 2014). Moreover, firms adopting the last-click model forfeit the chance to better optimize their ad spend(Moe and Fader, 2004). With increasing recognition of the role of digital advertising as an effective ad strategy, and in response to the above criticisms, the advertising industry proposed the alternative concept of multi-channel attribution (MCA). This framework assumes that more than one channel impression (or touch point) can each have a fraction of the credit for a sale based on the true inﬂuence each impression has on the conversion (Lovett, 2009). The underlying assumption is that individual ad channels should not be evaluated in isolation and credit must be assigned equitably with respect to the campaign goals on these channels. Industry analysts also claim that the MCA strategy calculates individual channel cost per acquisition (CPA) figures that are much closer to reality (Lovett, 2009), providing a better understanding of sales cycle length and the purchase funnel. For instance, Google (2012) recommends using the last-click model if “ads and campaigns are designed to attract people at the moment of purchase.”

In this paper, using an online firm’s purchase conversion data, we examine the nature and scope ofthese *rule-based* attribution models in measuring the performance of online channels in customer journeys. Moreover, we employ a statistics-based attribution model for online businesses, and shed light on how multi-channel attribution models can be used to better measure advertising performance. We develop hypotheses that examine at what stage in a consumer’s journey different online channels feature most prominently for an online business; the financial importance of these channels under last-click models; and the effects of moving to the *rule-based* multi-channel attribution models (i.e., time-decay, uniformly distributed and position-based) and statistics-based multi-attribute models. More specifically, we investigate: (1) whether multi-channel attribution models give different channel valuations than last-click models; (2) whether these channel valuations vary significantly between the various multi-channel models; and (3) whether statistical multi-attribute models have predictive validity. We consider the convergent validity of multi-channel models and discuss the forecasting ability of the statistical model as measured by predicting to a holdout sample.To date, the effect of changing attribution models for different online channels remains largely unstudied; therefore, an analysis of these models will offer conclusions on whether an advertising format’s revenue significantly differs depending on the model used. Extant literature provides generalizable insights on individual channel effectiveness (Kireyev et al., 2016); whereas, in this research, we use data to compare different models’ abilities to predict to the holdout sample and then directly compare with the ‘best’ model identified. Using these insights, we also show how different online sales channels should be credited for the conversion event, and to what extent?

The paper is organized as follows. We first examine various existing and proposed attribution models in relation to online advertising. We then assess at what stage in a consumer’s journey a particular media channel features most prominently for an online business. Empirical results on the outcomes of different attribution models are then presented in the next section. The study concludes by considering implications for different online sale channels and attribution.

**Attribution in Digital Advertising: A Literature Survey**

There can be multiple vendors, publishers or search engines (herein called channels) that serve advertisements. In a purchase funnel, therefore, there can be a number of touch points or channel impressions with digital advertising. If there is only one channel impression, such as an iTunes movies purchase, it is unlikely that attribution models will vary significantly in their predictions. Attribution modeling becomes interesting only when we consider the impact of severalchannelimpressions together. In the case of a cosmetic product, for example, customers are likely to read blogs, click display ads or search branded products before making a purchase decision. Their online journeys may take them to various different channels, where they make contact with advertising media and formats: ad campaigns may be run on a wide variety of online marketing channels such as social media and search, each of which may be important in customer journeys. To deal with these complex interactions, attribution models are employed that can reduce some of these complexities to their basic components by focussing on each stage of a customer’s journey that results in a purchase. As different advertising formats may differ in their total revenue effect, their influence may vary depending upon the particular stage of the purchase funnel. The process of attribution can thus be understood as the assignment of conversion credit when multiple ad channels reach a given online user. One may then apply multi-channel attribution models that aim to find the optimal mix of digital advertising channels that provide the highest return on investment (ROI). By tracking all the clicks in the stream, these models distribute the transaction’s sale value across all channel impressions in accordance with their added value.

We depict the problem of consumer interactions with different advertising forms in Figure 1.Suppose a web surfer clicks a display ad and makes a purchase (Case 1). The question of whether the display ad affects the consumer purchase decision is trivial and can be measured by simply looking at purchase conversions. In the second scenario (Case 2), a consumer visits display ad, paid search, social media, and price comparison sites before taking a buying decision. Do visits to all these channels have equal effects on a conversion? Or do they vary depending on various contextual factors? If indeed it is the case that channel visits have differential effects, then how can one assign credit to each of those consumer interactions?If the credit is all given to display, there are negative downstream effects (e.g. money be reallocated from other productive channels) due to the lack of the ‘assist’ from the other channels, including paid search, social media, and price comparison sites. Conversely, the less valuable channels could attract more credit than they deserve if one applies an arbitrary rule to assign credit for conversion. This may also lead to inaccurate advertising-spend calculations by the marketing departments as when they allocate budget across multiple forms of advertising.

[Insert Figure 1 about here]

*The role of online sales channels in the customer journey*

A customer can take different choice actions at different stages of a purchase funnel. For example, there can be three roles in a customer journey - ‘*introduction*’, ‘*assist*’, and ‘*conversion*’ (IAB, 2011; Chandler-Pepelnjak, 2010). *Introduction* plays the initial role in starting the process, often populated by search. Consumer behavior tends to be ‘exploratory’ at this stage. The second role is that of *assist*, being any contributing website that enables a transaction after the introduction and before the conversion. At this stage, consumer behavior turns to a ‘goal directed’ search (Kireyev et al., 2016). The *conversion* is final step before the purchase is made. The presence of more than one marketing channel raises the question of which of these channels features prominently at different stages of the purchase funnel (Chandler-Pepelnjak, 2010). As digital ads are automated, these channels can monitor which links are catching readers’ attention.

As noted,many existing credit assignment methods such as the last-click suffer from the fundamental problem of attribution - they do not take into account the impact of all those ad formats that were visited by a consumer contemplating a purchase (Wiesel, Pauwels and Arts, 2011).When a consumer enters a generic keyword ‘notebook’ in a search engine, the search will return paid ads by electronic retailers with links to branded notebooks as well as organic results on the search results page. Now assume that the searcher had already seen a link in a displayed ad format, decides to click on it, and converts (as discussed in Case 2 above). It is clear that both the displayed ad and the paid ad were on the path that led to the actual purchase - the consumer moved down the conversion funnel from displayed ad to paid ad. A rapidly growing body of literature thus examines the entire clickstream history of individual consumers in terms of whether visits to different ad formats have positive effects that accumulate toward a purchase (e.g., learning about a product that the shopper intends to buy; see Moe and Fader, 2004). This strategy of modeling the purchases resulting from the accumulative effects of all previous interactions largely focuses on how non-purchase activities (e.g., advertisement clicks, website visits) affect the probability of purchasing. Consequently, these models cannot directly deal with the question of attributing credit for conversion to each individual ad form.

It will also be difficult to observea cross-channel effect in an interactive situation: for example, Yang and Ghose (2010) show how paid search and organic search may complement each other in the purchase funnel. There is thus scope for additional research to figure out if such complementarity effects exist in other online mediums. Wiesel et al. (2011) measure cross-effects of online and offline media in terms of how customers move through the ‘purchase funnel’. They find a very high sales elasticity for AdWords (4.35), and much lower sales elasticities of .05 and .04 for flyers and faxes – other sales channels – respectively. Li and Kannan (2014) use a probit-based consideration and nested logit formulation for visit and purchase to attribute conversions. This and other related models (see Xu, Duan and Whinston, 2014, for mutually exciting point process models) have generally emphasized the classiﬁcation accuracy of different channel contributions; which means that they often omit the stability characteristic of the variable contribution estimate. Furthermore, these models do not study how higher exposure in one channel (e.g. display) may lead to higher level of activity in another channel (e.g. search clicks) (Anderl et al., 2016; Kireyev et al., 2016). In addition, there is a need to investigate whether online advertising effects differ by stage in the purchase funnel as earlier models did not treat online advertising effectiveness from this ‘stages in the purchase funnel’ perspective (e.g. Li and Kannan, 2014).

**Attribution models**

In the following, we first describe the four rule-basedmodels that can be used for measuring the performance of an ad campaign - the last-click, time-decay, uniformly distributed and position-based models. As can be seen, the last three models are multi-channel attribution models. All these models are populated with both advertisers and search engines as many users’ homepages are search engines (Google, 2012). Companies may use campaign data to assign the percentage of credit based on one or the other model. We then evaluate the assumptions of a statistics-based attribution model within the context of an advertiser’s goal of achieving the optimal conversions.

*The last-click model*

As digital advertising grew in the 1990s, the last-click model emerged as the industry’s main ad measurement tool. It ascribes 100% of the credit to the last ad the user clicked on before a purchase conversion (Xu et al., 2014). With regard to Case 2 above, display, paid search, and social media would get nothing at all under this model; instead it would attribute the entire conversion to price comparison.The strength of the last-click model lies in its ability to help determine which channels best lead users to a buying decision or final conversion. It thusprovidesa simple and elegant way to determine the credit assignment of each positive user, and previously becamethe fastest way to infuse confidence into the efficacy of digital advertising campaigns. A notable drawback of the last-click model is that it does not take into account many vital interactions and steps in a customer’s journey to transaction. From a complete journey perspective, it can be seen that the last-click attribution model unfairly rewards the sites at the end of a customer journey. This has prompted both marketing practitioners (Clearsaleing, 2014; Lovett, 2009) and researchers (Wiesel, et al., 2011) to consider alternative approaches such as multi-campaign methods that attribute credit to “all online marketing exposures that resulted in a conversion.” The ‘multi-channel’ attribution models assign credit to multiple channels when a number have been observed showing an advertisement to a converting user (Moe and Fader, 2004). In other words, credit is assigned to more than just one advertisement impression for driving the user to take a desirable action such as making a purchase. The idea is to allow an advertiser to share credit amongst the websites that influenced the transaction at any stage. The multi-channel models and their underlying assumptions are described in Table 1.

[Insert Table 1 about here]

*The time-decay model*

As a multi-campaign attribution framework, the ‘time-decay’ model adjusts credit so that the closer an impression is to a conversion, the more credit it receives. As the credit progressively increases in value across the customer journey, it nicely distinguishes itself from the last-click model (Clearsaleing, 2014). Under the time-decay model, the rewards can be apportioned so that the last contributor achieves maximum credit.For channels in Case 2, the time-decay model calculates value by progressively attributing more credit to the impressions closer to conversion - that is, price comparison. As the credit increases with time from initial discovery to final conversion, the model captures an important aspect of the consumers’ online behavior; that conversions are associated with a short attention span[[1]](#endnote-1). This *rule-based* attribution model follows the triangular numbers ratio of 1:3:6:10. Therefore in order to calculate the ratio breakdown for different length journeys we use the following formula:

(1)

In the above formula, the use of ‘n’ represents what step number it is; ‘Tn’ is the weighting given to it, and the 100% commission is divided up depending on the ratio. For example, a three-step journey will be divided up under the ratio of 1:3:6, with 10%, 30% and 60% attributed to the steps in chronological order. For each marketing tool, the revenue generated is then totalled to show the revenue generated by that tool for the time-decay model. It can be envisaged that those marketing channels that ‘close the deal’ as quickly as possible benefit more from this attribution strategy as the value is progressively weighted higher for channels nearest to the last impression. Therefore, it is argued that the time-decay model is particularly useful for short-lived deals or promotional offers (Lovett, 2009).

*Uniformly distributed attribution model*

In a uniformly distributed multi-impression attribution model, the value of each conversion is uniformly distributed to all impressions. Considering Case 2 above, the uniformly distributed model would attribute 25% of the conversion to each of the four channels involved. As the shares of each conversion are divided equally among all channels, the model does not consider where the touch points occur. Thus, the model’s assumption that each interaction in the customer journey has equal influence on the user’s purchase decision is not valid given that there may be varying influences of all such interactions. The model is motivated by the concern that the intrinsic value of each impression cannot be easily credited, even if the influence of each impression is significant enough in a purchase conversion. Therein lies the advantage of an equally weighted attribution model. It simplifies the attribution process by assuming that each impression contributes equal value to the conversion.

*The position-based model*

A popular version of the position-based model uses a Pareto distribution rule, whichattributes value to specific parts of the customer journey.The Pareto distribution model places more importance on the first and last touch points than on all the others in between. For example, under the 80/20 rule, 80% of the conversion value is credited to the first and last touch points while the remaining 20% is distributed to the other channels in the customer journey.Therefore, in relation to Case 2, display and price comparison would be assigned 80% of the value of conversion, while paid search and email would only get 20%.The model assumes that the first impression is important because it attracts the user’s attention; and the last one is important because of the role it plays in concluding the transaction.The remaining impressions can be evaluated equally low in their impact. A major strength of the model is that each channel’s importance is individually determined in relation to the specific goals of an advertising campaign. A higher value may be assigned to the first interaction because, in some situations, numerous leads may need to be generated and the campaigns are more focused on creating awareness.As the middle contributors receive value as well as the first and last clicks, the method offers an adequate response to the criticism that rule-based models remove brand value (Lovett, 2009). However, despite emphasizing the role of all agents in value creation, the model is still heavily biased toward the first- and last-click channels.

*Statistics-based attribution model*

Shao and Li (2011) observe that many existing models are mostly concerned with calculating channel effectiveness in multi-channel settings, whereasattribution models should ideally be able to correctly predict conversion events. In this section, we describe a statistics-based multi-attribute approach that is based on empirical observations rather than theoretical assumptions. In the light of the increasing complexity of digital advertising, researchers have, in recent years, endeavored to develop a true data-driven methodology to account for the inﬂuence of each user interaction on the ﬁnal user decision. For example, Shao and Li (2011) have developed a probabilistic model based on a combination of ﬁrst- and second-order conditional probabilities. There are two steps involved in generating this model:

The empirical probability of the main factors (i.e. the probable use of different media channels) is calculated as follows,

*P(y|xi)=* (2)

and the pair-wise conditional probabilities

*P(y|xi, xj)= ,* (3)

for *i ≠ j*.

A conversion event (purchase or sign-up) is denoted as *y* which is a binary outcome variable, and *xi,i = 1,...,p,* denote *p* diﬀerent advertising channels. *Npositive (xi)* and *Nnegative (xi)* denote the number of positive or negative users exposed to channel *i*, respectively, and *Npositive (xi, xj)* and *Nnegative (xi, xj)* denote the number of positive or negative users exposed to both channels *i* and *j*. Customer journeys contain one or more touch points across a variety of channels. The channels actually visited by the consumers out of the many channels involved will give us information on the number of ‘positive’ and ‘negative’ users in a purchase funnel.

The contribution of channel *i* is then computed at each positive user level as:

*C(xi) = p(y|xi) +* (4)

where *Nj≠i* denotes the total number of *j*’s not equal to *i*. In this case it equals to N-1, or the total number of channels minus one (the channel *i* itself) for a particular user.

As there is significant overlap between the inﬂuences of different touch points due to the user’s exposure to multiple media channels, the model fully estimates the empirical probability with the second-order interactions. An advantage of using the above estimation is then that it includes the second-order interaction terms in the model. Dalessandro, et al. (2012) show that, after rescaling, this probability model is equivalent to theirShapley Value formulation under certain simplifying assumptions. In a typical Shapley Value cooperative game, a group of players generates a shared ‘value’ (e.g. wealth, cost) for a group as a whole (Osborne and Rubinstein, 1994). The Shapley Value of a player in a game is calculated as their expected marginal contribution over the set of all permutations on the set of players; in other words, the Shapley Value of an advertising medium is its expected marginal contribution over all possible sets of the interacting channels.

**Research Objectives**

An advertising campaign may be designed in a way that it induces a customer to visit different online channels until a product or service is finally purchased. Prior literature as discussed above indicates the differential effectiveness of different advertising forms; however, the effect of changing attribution models for these various forms remains mostly unstudied. This is largely because many such enterprises use the last-click attribution model (Clearsaleing, 2014). The focal firm also uses the last-click model as a default attribution strategy, meaning that we can focus on assigning value to a particular channel and then compare the effects of moving to time-decay, uniformly distributed, position and statistics-based attribution models against the current last-click model. Our specific hypotheses consider:

* whether multi-channel attribution models give different channel valuations than last-click models;
* whether these channel valuations vary significantly between the different multi-channel models; and
* whether statistical multi-attribute models have predictive validity.

Among other things, our findings will shed light on whether last-click attribution models should be discarded in favor of multi-channel attribution models. As part of these investigations,we consider the convergent validity of multi-channel models and discuss the forecasting ability of the statistical model as measured by predicting to a holdout sample.

To implement our research, we consider whether an advertising format such as display generates more revenue under the last-click model than it would under a multi-channel attribution model such as time-decay model (or any other multi-channel attribution models for that matter). This is motivated by the observation that display may act as a converter in the purchase funnel; and since the last-click model attributes 100% credit to a converter, all credit will go to this online channel. In their study of digital channel effectiveness, Kireyev et al. (2016) find that display ads increase search conversion.To examine the differences between display and the other online marketing channels, we assess whether both groups’ means statistically differ, with reference to the average order value. We also look for any significant difference between the revenues attributed to the online channels. In our data, we have information about several key aspects of digital marketing tools. For example, display or banner ads are used for both direct response and branding styles of marketing. The retargeting ﬁrm maximizes the purchases per dollar spent on ad placements by choosing the most cost effective placements. Email campaigns and retargeting can be used effectively depending upon the specific goals of an advertising campaign and the performance metrics used to gauge the campaign’s effectiveness.

**Methods**

In this section, we utilize logs from a large-scale online sales platform to first identify where different online channels feature in customer journeys. In total, we include 996,708 transactions in the analysis, with total revenue of $158,519,417, at an average order value of $112.5. In terms of the customer journey lengths; 65.95% are one step, 14.58% two step, 8.78% three step, 3.86% four step, and 6.84% five steps or more. Our conversion data span 104 weeks from 1 January 2012 to 28 February 2014. Currently, the investigated firm attributes revenue generated through online transactions to its various paid marketing tools on a last-click basis. As we test the multi-channel attribution models that look at touch point sequences, our data contain the full set of touch points; we thus have information about complete consumer journeys (the list of individual touch points is provided below. Appendix I gives several examples of this data collection process). Data on the following eight most common online marketing channels were collected:

1. Display ad transaction consisted of any visitor that originated (i.e. visitors whose prior clickstream includes that channel) from display ads posted on any third-party non-search web domain.
2. Organic search transaction consisted of any visitor that originated from an organic (non-paid) search on a web search engine.
3. Paid search transaction consisted of any visitor that originated from a pay-per-click (PPC) advertisement on a web search engine.
4. Price comparison transaction consisted of any visitor that originated from a price-comparison site.
5. Email transaction consisted of any visitor that originated from email.
6. Retargeting transaction consisted of any visitor that originated from retargeting (retargeting is never the only step in a sales journey).
7. Social medial transaction consisted of any visitor that originated from a social media website.
8. Others; including transactions that consisted of any visitor that originated from a manual URL entry into a web browser.

It is important to acknowledge that, depending upon the product category, offline channels (e.g., word-of-mouth (WOM), bricks-and-mortar store visits) are also important parts of the information chain. However, WOM and bricks-and-mortar visits are not contained within our data as our focus is on online channel valuations[[2]](#endnote-2). We divide our sample into two subsamples in order to validate our results: one for estimation of the model and another for validation purposes. We first parameterize our models, and then fit them to two thirds of the data and test a holdout sample. Subsequently, we choose the model that fits and predicts best. We define our conversion measures as follows:

Purchase conversions: Number of final sales transactions generated by the online sales channels ads.

Purchase conversion rate: Percentage of purchase conversions on ad impressions out of the total number of times that ads are clicked.

**Results**

*Descriptive statistics*

We first present the contributions of different online marketing tools to online revenue under the last-click model in Table 2. As discussed, the model attributes all conversions to the last referring impression within a customer journey, which means it is the final interaction that matters from a marketing perspective. It can be seen from Table 2 that when using the current last-click method, the highest revenue generating online marketing tool is that of organic search, bringing 63%. Social media contributes the least with the current model, at 1%. In other words, organic search is the biggest contributor to firm revenue, more than display and other media channels. The table also sheds light on social media’s relatively small contribution to the firm revenue; however, this was expected from our data as social media is still an emerging new media channel in many different sectors of the economy. Another important finding is that the mean order value for display is higher than any other of the marketing tools at $159. In addition, our data show that display features most prominently as the converter as 39.08% of display ads in the sample act as a converter (Chandler-Pepelnjak, 2010), being the last step in a multi-step customer journey. Furthermore, 22.59% of all converters in online marketing are display ads. Display features least prominently when undertaking the role of introducer (11.30%)[[3]](#endnote-3).

[Insert Table 2 about here]

*Main results*

To examine whether multi-channel attribution models give different channel valuations than last-click models, we conduct two-sample t-test comparing average order values of different online marketing tools under different multi-channel attribution models. We first examine the time-decay model as developed by Google (2012); it credits most of the sites along a customer journey, but places increasing emphasis on the steps closest to the transaction. Figure 2 displays the effects on revenue for online media channels if the time-decay model was introduced. Similarly to the last-click model displayed in Table 2,organic search leads the way, contributing 61.27%. Display ads represent 14.68% of the revenue generated, down on the 20.30% revenue accumulated under the last-click model. Email and social media see the largest change in value percentage, seeing increases of 197.67% and 435%, respectively. Table 3 shows how much revenue is allocated to display using all five attribution models. Our results do not change if we consider any other online media channel instead of display. The first column is the mean of revenue that each method attributes to display, and the second is the difference between the last-click and the four other attribution methods revenue. As we find, there is a considerable difference in the mean revenue of the five models with time-decay trailing last-click to a large extent. A contributing factor could be that the last-click model allocates 100% of the revenue to the last media channelin customer journeys. In contrast, the-time decay model offers varied percentages. We conduct a two-sample t-test comparing last-click and time-decay average display rewards. The t Stat of 25.397 is greater than the two-tail critical value of 1.960, therefore indicating (with a 95% confidence level) a significant difference between the average display ads reward. Accordingly, it could be concluded that the time-decay model on average attributes lower revenue to display. This is supported by Table 3 that shows displayed ads are allocated 14.55% lower revenue under the time-decay model. These results suggest that the time-decay model as a multi-channel attribution model gives different channel valuations than the last-click model.

[Insert Figure 2 and Table 3 about here]

The uniformly distributed model follows the last-click and time-decay models, collating the revenue for each online media channel to sum their overall contribution to online marketing in the weighted average format. Figure 3 represents the effects on the attribution of revenue for online media channels using the uniformly distributed model. Organic search continues to dominate the revenue streams, followed by display and paid search. A decrease in display revenue from the last-click model and the time decay model is evident. Display contributes 14.12% of the revenue, a decrease of 23.34% from the last-click model. Price comparison, email and social media continue to see increases in revenue percentages from the last-click model, at 53.95%, 154.65% and 415%, respectively.We conduct a two-sample t-test comparing last-click and uniformly distributed average display rewards.The t Stat of 30.804 is greater than the two-tail critical value of 1.960, therefore indicating (with a 95% confidence level) a significant difference between the average display rewards. Consequently, it could be concluded that the uniformly distributed model on average attributes lower revenue to display. This is supported by Table 3 that shows display ads are allocated 25.46% lower revenue under the uniformly distributed model. Employing linear regression, we further carry out hypothesis testing of the difference between means using the t-test. As previously, these findings confirm that the uniformly distributed model as a multi-channel attribution model gives different channel valuations than the last-click model.

[Insert Figure 3, 4 and 5 about here]

The position-based (sometimes called Pareto distribution) model, a relatively new attribution approach, attributes credit for purchase conversion to specific parts of the customer journey. Figure 4 reflects revenue attribution for online media channels using the position-(or Pareto) based model. Organic search continues to dominate the online marketing tools with 63.47%. Display dominates among the paid marketing tools, being responsible for 13.65%, representing a 25.89% decrease on the last-click model. As seen in the other models, social media continues to contribute the least revenue; however, it still reflects a 295% increase on the revenue generated in the current last click model. Retargeting is fairly consistent with the last-click model, slightly increasing from 1.22% to 1.78%. Moreover, paid search sees a sizeable increase in proportional revenue from 10.92% to 13.88%. We conduct a two-sample t-test comparing last-click and position-based average affiliate rewards. The t Stat of 29.913 is greater than the two-tail critical value of 1.960, therefore indicating (with a 95% confidence level) a significant difference between the average display rewards. We may then conclude that the position-based model on average attributes lower revenue to display. This is supported by Table 3 that shows display ads are allocated 23.73% lower revenue under the position-based model. We can thus conclude that the position-based model as a multi-channel attribution model gives different channel valuations than the last-click model.

Figure 5 shows the effects on revenue attribution for online media channels using the statistics-based model. Our results show that display represents 14.34% of the revenue generated, down on the 18.42% revenue accumulated under the last-click model, whereas organic search registers a decrease from 63.45% to 60.84%. Social media and email record the largest changes in value percentage, as reflected in their revenue generation contributions of 3.67% and 3.38%, respectively. There is also a sizeable increase in paid search, from 10.92% under the last-click model to 12.85% under the probability model. We conduct a two-sample t-test comparing last-click and probability based display rewards.The t Stat of 28.435 is greater than the two-tail critical value of 1.960, therefore indicating (with a 95% confidence level) a significant difference between the average display return. We may then conclude that the statistics-based attribution model on average attributes lower revenue to display. This is also supported by Table 3 that shows that display ads are allocated 24.86% lower revenue under the statistics-based attribution model. Employing linear regression, we further carry out hypothesis testing of the difference between means using the t-test. The R2 of 0.456 and adjusted R2 of 0.321 in Table 4 explain well our response variable (average order value). Furthermore, F = 808.264 in the regression analysis is equal to the square of the t Stat (28.435) from the t-test, which is consistent with Property 1 of F Distribution. All these results provide support to our first hypothesis. In order to examine whether channel valuations differ significantly between the various multi-channel models, we provide correlation data analysis in Table 3. As can be seen from Column 4 and 5, there are higher correlations among the channel valuations of different multi-channel attribution models. That is, the differences between multi-channel models are not that great except for the smaller channels.The results verify the convergent validity of the multi-channel approach.

In addition to the forecasting accuracy of models fit to past data in Table 4, we use a hold-out sample to validate our results. As discussed above, we divide our sample into two subsamples: one for estimation of the model and another for validation purposes. The procedure we apply is to first parameterize our models, and then fit them to two thirds of the data and test the holdout sample. Consequently, we can compare different models’ abilities to predict to the holdout sample. The resulting model fit statistics are presented in Table 5. As we find, Model 5 (statistics-based attribution model) provides a better fit to the data than the other models do, confirming our final hypothesis. This can be seen from the low MAPE (Mean Absolute Percent Error) and MAE (Mean Absolute Error) for the statistics-based attribution model.

In Table 6, we present logistic regression results for various online channels. The regression predicts order/no order. As expected, all major online channels including organic and search show greater contributions toward final conversions, providing further support to our earlier results. In summary, all the multi-channel models show that the last-click model overstates an online channel when it is acting as a converter, and the differences between multi-channel models are not that great except for the smaller channels. Also, the MAPE (Mean Absolute Percent Error) and MAE (Mean Absolute Error) are quite low, which enhances the predictive validity of the statistical approach, and this in turn enhances the convergent validity of the multi-channel approach.

[Insert Table 4, 5 and 6 about here]

**Discussion and Conclusions**

Evidence shows that multiple touch points or funnel stages are typically required before purchase and that these touch points have different effects on purchase likelihood (Xu et al., 2014). We examined the hypothesis that multiple digital channels or touch points generate more revenue under the last-click attribution model than uniformly distributed, time-decay, position-based and statistics-based models. In particular, we compared the effects of moving to time-decay, uniformly distributed, position-based and statistics-based attribution models against the current last-click model.The results show that the last-click model generates the most revenue for the converter and delivers the highest average reward. When comparing the last-click model against each one of the other models, the t-tests showed a significant difference in the average channel reward value, with the last-click model attributing significantly higher to the display channel. Therefore, both the revenue and average channel reward values showed a significant difference between the current model and the others explored.

The revenue attributed to display declines (on average 22.15%) when moving to the other attribution models from the current last-click model. The largest such decline is seen in the uniformly distributed model, 25.46%. Previous research failed to explain this phenomenon, except for the suggestion that a modeling approach such as the uniformly distributed one confirms the relevance of the entire sales cycle, as when one channel predominantly plays the role of the converter (Havas Digital, 2010). Therefore, any activity that takes credit away from the converter is likely to be to the detriment of that channel’s revenue. We conclude from this analysis of the multi-channel models that the last-click model overstates display (or any other online marketing tool when it acts as a converter), and the difference between multi-channel models are not that significant except for the smaller channels.

Moreover, the problem with any rule-based attribution model is that not only is it impossible to predict (on an individual basis) the ways customers across multiple backgrounds make purchases but also how the shared value can be allocated equitably among the players according to their individual contributions. Given these constraints, it will be too complicated to develop an attribution model for each and every path to purchase (Shao and Li, 2011; Anderl et al., 2016; Blake et al. 2015). Consequently, one may have to consider the more rigorous variety of statistics-based attribution models as a preferable attribution strategy. These models allow one to provide more stable credit assignments to the digital channels in a purchase funnel: this is evidenced from the forecasting ability of the statistical model as measured by predicting to a holdout sample. In our present context, our findings enhance the predictive validity of the statistical approach, and this in turn enhances the convergent validity of the multi-channel approach. However, as we also value each medium for its contribution to the end purchase, our study understates the value of some key emergent media in the chain, particularly social media. It appears that the attribution models currently do not fully value social media, which often do not directly lead to purchase but can have a strong behavioral impact, for example, by shaping the consideration set. While the value of social media does improve as the sophistication of the attribution models increases, the consumer behavior implications need to be fully accounted for in future research.

*Implications for marketing managers*

The most frequently employed attribution strategy is the last-click model. This measurement strategy has significant consequences for all paid advertisers, particularly as it can be readily used to justify online ad spend in comparison to the budget for offline media such as television.However, a major drawback of this attribution model is that it undervalues the consumer click activity that may have preceded the last-click leading to a purchase conversion. Since consumers typically search multiple times before making a purchase, the model attributes final search queries more conversions than they deserve. This suggests that a better understanding of the purchase funnel will drive smarter marketing campaigns generating a higher return on ad spend. Multi-channel attribution models have evolved to reflect the growing complexity of attributing credit with each new advertisement format. An advantage of a campaign-based or a rule-based attribution model is that it can be customized to the specific goals of a digital marketing campaign. As these models allow each click in a stream, not just the last click, to receive credit for a conversion, understanding their true value allows an advertising manager to optimize their online spend and establish a higher level of accountability. However, as we demonstrate here, these models are based on a number of weak and limiting assumptions. Although an advertising campaign may find that the simplicity of the time-decay multi-impression model or the last-click model has significant advantages over other models, the question remains of whether they accurately attribute credit to all the channel impressions in a purchase funnel. Our empirical study of a statistics-based attribution model suggests a direction that companies can take when attributing credit to different channels in a purchase funnel. In particular, we expound the way a statistics-based attribution model provides stable and accurate interpretations of the influence of each user interaction, although it must be recognized that attribution primarily takes a retrospective view (Kireyev et al., 2016; Shao and Li, 2011).

The problem of attribution modeling can be defined as aligning the incentives of the advertiser with those of the channels hired to run ads on behalf of the advertiser. Whereas an advertiser wants to drive as many conversion events at as low a cost as possible, the channels would like the conversion events that the advertiser observes to generate the highest profit possible. It is in this context that we focus more on accurate and stable interpretations of the inﬂuence of each user interaction on the ﬁnal user decision rather than just on user classiﬁcation. As we argue, we can achieve this by implementing a statistics-based attribution model that provides stable and accurate interpretations of the influence of each user interaction, a goal that cannot be achieved when using a rule-based attribution model. For example, we have examined the assumptions of several attribution models in how they assign credit to different online channels in a purchase funnel. We consider the contribution of the convergent validity of the multi-channel models as well as the predictive ability of the statistical model. Our results show that display loses value under last-click models and multi-channel methods are consistent with each other in how they assign credit to different online channels. We are thus able to offer guidance on aggregate-level budget allocation decisions across multiple forms of advertising.

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**Table 1. Multi-channel attribution models**

|  |  |  |
| --- | --- | --- |
|  | **Attribution model** | **Modeling approach** |
| 1 | Time-decay Model | Rule-based modeling assumptions |
| 3 | Uniformly Distributed Attribution | Rule-based modeling assumptions |
| 2 | Position-based Model | Rule-based modeling assumptions |
| 4 | Statistics-based Model | Cooperative game theory-based modeling assumptions |

**Table 2: Different online marketing tools and revenue generated under last-click method.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Tool** | **Revenue (%)** | **Orders (%)** | **Average Order Value (in dollars)** |
| Organic Search | 63 | 67 | 106 |
| Display | 18 | 13 | 159 |
| Paid Search | 11 | 10 | 116 |
| Others | 3 | 3 | 113 |
| Price Comparison | 2 | 2 | 136 |
| Retargeting | 1 | 2 | 110 |
| Email | 1 | 1 | 112 |
| Social Media | 1 | 2 | 48 |

**Table 3: Display ads revenue from uniformly distributed, position-based, time-decay and statistics-based attribution compared to last-click attribution.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Tool** | **Display Ads Revenue** | **Last-click Difference** | **Increase/decrease from Last-click** | **(UD)** | **(PO)** | **(TD)** | **(SB)** |
| Last-click | 30 | n/a | n/a | n/a |  |  |  |
| Uniformly distributed (UD) | 22 | 8 | -25 |  |  |  |  |
| Position (PO) | 23 | 7 | -24 | .76 |  |  |  |
| Time- decay (TD) | 25 | 4 | -15 | .78 | .75 |  |  |
| Statistic-based (SB) | 23 | 7 | -25 | .63 | .66 | .67 |  |

**Table 4: Statistics-based model: t-Statistics and regression results**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Coefficients** | **Std. Err** | **t Stat** | **P-value** | **Lower 95%** | **Upper 95%** |
| Intercept | 27.983 | 1.278 | 19.543 | 4.762 | 13.754 | 21.956 |
| Display | 4.487 | 1.365 | 28.435 | 1.9E-139 | 9.738 | 0.287 |
| F  Multiple R  R Square  Adj R Squ  Std Err  Observations | 808.264  0.534  0.456  0.321  2.783  783,564 |  |  |  |  |  |

**Table 5: Model fit: Using hold-out sample**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Statistic** | **Model 1**  **(last-click)** | **Model 2**  **(time-decay)** | **Model 3**  **(uniformly distributed)** | **Model 4**  **(position-based)** | **Model 5**  **(statistics-based)** |
| Sum of square error | 926.473 | 923.593 | 917.739 | 912.166 | 821.249 |
| Mean absolute percent error | 3.365 | 3.489 | 3.765 | 3.387 | 3.256 |
| Mean absolute error | 6.546 | 6.678 | 6.894 | 6.785 | 6.364 |

**Table 6: Logistic regression results**

|  |  |  |  |
| --- | --- | --- | --- |
|  | **B** | **EXP(B)** | **Marginal effects** |
| Intercept | −4.245\*\*\* | .005 |  |
| Organic Search | .436\*\*\* | 1.762 | .0138\*\*\* |
| Display | .174\*\*\* | 1.241 | .0014\*\*\* |
| Paid Search | .358\*\*\* | 1.489 | .0127\*\*\* |
| Price Comparison | .472\*\*\* | 1.683 | .0145\*\*\* |
| Retargeting | .394\*\*\* | 1.365 | .0022\*\*\* |
| Email | .147\* | 1.126 | .0013\* |
| Social Media | .135\*\* | 1.113 | .0019\*\* |
| Observations | 783,564 |  |  |

⁎ *p* < .05.

⁎⁎ *p* < .01.

⁎⁎⁎ *p* < .001.

Case 1: -------------------------------------------------------------------------------------------

Display ads Purchase

Case 2: --------------------------------------------------------------------------------------

Display ads Search Social Media Price Comp Purchase

**Figure 1: Purchase conversions in a sales funnel**

**Figure 2. Online revenue generation using time-decay attribution modeling**

**Figure 3. Online revenue generation using uniformly distributed attribution modeling**

**Figure 4. Online revenue generation using position (or Pareto) attribution modelling**

**Figure 5. Online revenue generation using statistics-based attribution modeling**

**Appendix I: Data collection (and model-based revenue distribution)**

First, we consider the example of last-click model-based revenue distribution using Microsoft Excel. As discussed, the last-click model is the most simplistic and straightforward method. If considering Figure.1a, the data highlighted are rewarded with the revenue stated. Consequently, the display ad gains the credit for driving the sale. This will always be the last step in the customer’s journey and in the case of a 1 step journey will be the only step.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 1st Step | 2nd Step | 3rd Step | 4th Step | Revenue |
| email | Retargeting | search | display ad | $51.00 |

Fig.1a. An example of a 4 step journey

To apply this model to all of the data, first they are separated into how many total steps in the journey (e.g. Figure.1a displays a 4 step journey). Using the sort function the data are placed alphabetically from the last cell (the rewarded cell) to group into the various online marketing tools such as email, social media and price comparison. From here the revenue for each online marketing tool can be calculated and then totalled for all the length of customer journeys. For instance, Figure.1b shows a cell representation of a 3 step journey using the time decay model (a 3 step journey will be divided up under the ratio of 1:3:6, with 10%, 30% and 60% attributed to the steps in chronological order). To calculate the total values, the revenue will be multiplied by the required percentage and then that amount allocated to that step.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Number of steps | 1st Step | 2nd Step | 3rd Step | 4th Step | 5th Step |
| One | 1 |  |  |  |  |
| 100% |  |  |  |  |
| Two | 1 | 3 |  |  |  |
| 25% | 75% |  |  |  |
| Three | 1 | 3 | 6 |  |  |
| 10% | 30% | 60% |  |  |
| Four | 1 | 3 | 6 | 10 |  |
| 5% | 15% | 30% | 50% |  |
| Five | 1 | 3 | 6 | 10 | 15 |
| 2.9% | 8.5% | 17.1% | 28.6% | 42.9% |

Figure.1b Time-decay attribution ratios and percentages.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Total Revenue | 1st Step | | 2nd Step | | 3rd Step | |
| $155.00 | email | $15.50 | search | $46.50 | website | $93.00 |

Figure.1c An example of a time-decay 3 step journey.

Figure.1c provides an example of a time decay 3 step journey. For each marketing tool, the revenue generated will then be totalled to show the revenue generated by that tool for the time-decay model.

**Notes**

1. Similarly, the importance of the impressions may decreases with time: in these cases, the closer an impression is to a conversion, the less credit it receives. [↑](#endnote-ref-1)
2. This is a matter for future research. [↑](#endnote-ref-2)
3. The fact that any customer journey longer than five steps is shortened to five may ignore some display ad introducers. This is an area that requires further exploration in future research. [↑](#endnote-ref-3)